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Mortality Curves for Road Wheels of Tracked Vehicles

February 1987 Albert Van Horn

TACOM

SYSTEMS ANALYSIS DIVISION

Systems and Cost Analysis Directorate

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This report presents methods for analyzing data from the Sample Data Collection (data base. The methods presented used order and extreme value statistics in the anal of multi-censored data. The analysis develops mortality curves for roadwheels of the and M60A3 tanks and for the M2/M3 vehicles.

The method presented is applicable to a broad class of component failures or repl ments recorded in the SDC data base and should provide a useful base for further analy of this type. Keywords:

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Table of Contents

Mortality Curves for Road Wheels

of Tracked Vehicles

Objectives

1. Develop mortality curves for the road wheels of the M1 Abrams, the M2/M3 Bradley, and the M60A3 Patton.

2. To use the mortality curves developed to evaluate the cost and availability impact of road wheel block change policies.

3. To determine whether or not block changes of road wheels of tracked vehicles such as M1 tank reduce maintenance cost and increase combat effectiveness.

Introduction

The development of failure or mortality curves requires a reliable source of failure data. Ideally one such source should be the Army's sample Data Collection (SDC) program. The purpose of the SDC program is to determine the performance of military equipment under actual field operating conditions. The intent is that this data would be used to estimate reliability and durability characteristics of the equipment under study. The SDC program maintains an M1, M2/M3, and an M60A3 data base. However, SDC is statistically an unstructured data source, and is subject to many biasing effects that would normally balance out in a well designed experiment.

Some characteristics of SDC that contribute to this biasing are: vehicles leave SDC before failures occur, SDC is a continuing program and not all the vehicles in the sample will have experienced failure, vehicles entering SDC may have different ages, and vehicles in SDC are not driven a set number of miles which results in the wide variation in usage. In addition the length of time a vehicle is included in SDC varies. Vehicles enter and leave individually and by units. Few if any vehicles are in SDC for the entire duration of the program.

These conditions and other biasing effects within SDC make accurate estimation of road wheel mortality under field conditions a difficult or inaccurate process. Estimates based on straight line averaging are likely to produce erroneous answers.

Methods of estimating failure distributions that account for these biasing effects and fit the inherent nature of the SDC program have been developed in recent years.(3)(5)(8). These methods include both graphical and analytical techniques. For the analysis of road wheel mortality data only the graphical techniques will be used

in this report. The advantages of the graphical method are that linearizing transformations can be made to fit the data to a straight line so that linear regression can be used to estimate the distribution parameters, and that it can be used to analyze both complete and incomplete observations. Complete data are the data generated when the failure times of all the units in a test sample are known. When the failure data includes the running times of both failed and unfailed units, the data is said to be incomplete. Incomplete data is also known as censored data. The censoring times are the running times of the unfailed units. Failure data such as the SDC data is known as multi-censored data when the censoring times of the unfailed units are different.

In addition to the problem of incomplete multi-censored data there is the problem of tracking failure times when more than one component is used in a system. In the case of road wheels 28 to 32 wheels are used on each vehicle.

It is difficult to identify secondary failures from SDC data, because it does not consistently report road wheel position data. To overcome this problem only the first failures are considered, subsequent mileage accumulated after the first road wheel failure is not considered. If in conducting a reliability test N groups of n components are subjected to a test, and the time to the first failure of each group is recorded, a prediction of the distribution of time to first failure can be made. Then using the Extreme Value (EV) method the failure distribution of the individual components can be estimated after N failures instead of Nxn failures. Since n can take all values from one to a very large number the methods developed in this report provide a general method for analyzing SDC data.

The Extreme Value method generates a mortality curve (failure curve) over time by fitting the first failure of a set number of tested samples to a cumulative failure distribution. SDC data can be used with the EV method by selecting those vehicles that have entered SDC and recording the miles to their first road wheel failure. This restricted vehicle sample data should be tested for biasing effects such as vehicle demographics, base environment, road wheel location on the vehicle, (i.e. inner or outer, fore or aft, left or right.), however, because of the limitations of the SDC data positional effects can not be tested, although there is collateral evidence that a strong front to back bias exists. The EV method assumes that the failure distribution remains constant throughout the life of the test sample since only the first failures are considered. The EV approach as developed in this report will provide the best possible estimate of the mortality curves for road wheels within the constraints of the SDC data.

Conclusions

1. The values in Table XII represents the best estimate of the parameters of the failure distributions of the road wheels current Army tracked vehicles. These values were developed using the smallest extreme value distributions of road wheel failures and results in the mortality curves in Figure 12. MMBF values are:

M1	6051 Miles
M60A3	6480 Miles
M2/M3	7831 Miles

2. Block changes of tracked vehicle road wheels increase the life cycle maintenance costs and do not substantially increase the vehicle readiness characteristics such as mean-miles-between unscheduled replacement and availability.

3. The SDC data does not permit analysis of mortality curves for the two aluminum road wheels used on the M60A3.

4. There is no significant base effect for road wheels for M1, M2/M3, and the M60A3.

5. There is no significant differences in road wheel mortality between the M2 and the M3.

Methods of Analysis

The methods used in this report to generate the road wheel mortality curves are based on several reliability techniques that have been developed for the analysis of test data. These methods can be broadly classified as order statistics and the statistics of extremes or Extreme Value theory. Order statistics can be used to fit the data to a linear transformation of cumulative distribution functions when the data are complete. If the data is not complete as in the case of SDC other methods must be used. The distribution function most often used and the one used in this report is the Weibull cumulative distribution.

Weibull Distribution

The Weibull distribution is widely used in reliability for life testing applications. Before it was used in life testing the Weibull distribution was known as the Fisher-Tippett Type III distribution of smallest values or as the third asymptotic distribution of the smallest Extreme Value. It became known as the Weibull distribution after Waloddi Weibull used it as a probabilistic characterization for the breaking strength of materials.

The Weibull distribution was introduced to the reliability community by the work of J. H. K. Kao in life-testing electronic tubes. Kao also developed Weibull probability paper as an aid in estimating the parameters of the distribution. The Weibull cumulative distribution function can be written as

$$F(x) = 1 - \exp(-(x/\text{theta})^{\text{beta}}) \quad (1.1)$$

and the Weibull probability density function as

$$f(x) = (\text{beta}/\text{theta})(x/\text{theta})^{(\text{beta} -1)} * \exp(-(x/\text{theta})^{\text{beta}}) \quad (1.1a)$$

where

beta = scale parameter

theta = shape parameter

The methods of analysis using Weibull probability paper are used in this analysis, however with the availability of digital computers and modern software the laborious plotting can be eliminated. The method of analysis was extended to mechanical devices by C. Lipson at the University of Michigan. The main advantage of the Weibull distribution is its flexibility.

If beta, the scale parameter, is equal to one the Weibull distribution reduces to the exponential distribution, and as beta approaches four the Weibull distribution approximates the normal distribution. The linear transformation used in the design of Weibull probability paper is:

$$\ln(\ln(1/(1-F(x))) = \text{beta}*\ln(x) - \ln(\text{theta}) \quad (1.2)$$

From the parameters beta and theta the mean and variance can be computed using the equations:

$$\text{Mean} = \text{theta} * \text{gamma}(1 + 1/\text{beta}) \quad (1.3)$$

$$\text{Variance} = (\text{theta})^2[\text{gamma}(1+2/\text{beta})-\text{gamma}^2(1+1/\text{beta})] \quad (1.4)$$

Order Statistics

Equation 1.2 is used to transform the data to permit the application of the linear regression procedure. From the slope and intercept of a linear equation the parameters of the Weibull distribution can be easily estimated. The method of ordering data and assigning cumulative probabilities used in this report is called median ranking. Other ranking methods such as mean ranking are some times used, but median ranking is preferred by most sources. An approximation to the median rank value is given by

$$m.r. = (j - .03)/(n - 0.4) \qquad (1.5)$$

where

n = number of units in the sample

j = the rank of the sample value when ordered

The linear transformation in equation 1.2 is then applied to prepare the data for regression analysis. The regression analysis that was performed using a statistical software package called the SCSS Conversational System. The scale parameter of the Weibull distribution is the slope of the regression line. The shape parameter is obtained by taking the inverse transform of the intercept of the regression line.

In the case of incomplete data several extra steps must be taken. Incomplete data, sometimes called suspended data, are handled by assigning an average order number to each of the failure times. The suspended items are not given increment numbers, but do contribute to the average order of the failed data. Accounting for this can be a time consuming task, however, a simplifying formula can be used to produce what is known as a new increment. The new increment I is given by

$$I = \frac{(n + 1) - (\text{previous order number})}{1 + (\text{number of items following suspended item})} \qquad (1.6)$$

To illustrate the method consider the following example.

Table I Suspended Test Data

Hours on Test	Sequence	Status
544	F1	Failure
663	F2	Failure
802	S1	Suspension
827	S2	Suspension
897	F3	Failure
914	F4	Failure
939	S3	Suspension
1094	F5	Failure
1099	F6	Failure
1202	S4	Suspension

The first two failure times have the order numbers 1 and 2 respectively. For the third failure a new increment must be calculated. Applying equation 1.4 yields

$$I = \frac{(10 + 1) - 2}{1 + 6} = 1.29$$

Adding I to the previous order number, 2, gives the order number 3.29 to the third failure time. The same increment value is used until the next suspended item is encountered, thus, the order number for the fourth failure is 3.29 + 1.29 = 4.58. Applying the formula to the fifth failure gives

$$I = \frac{(10 + 1) - 4.58}{1 + 3} = 1.60$$

The position for the fifth failure is 4.58 + 1.60 = 6.18 and the position for the sixth failure is equal to 7.78. The final data for plotting is given in Table II.

Table II Ranks for Suspended Test Data

Hours on Test	Position	Median Rank
544	1.00	0.067
663	2.00	0.163
897	3.29	0.288
914	4.58	0.411
1084	6.18	0.565
1099	7.78	0.707

The data in Table II is transformed using the linearizing transformation

$$x = \log(\text{Hours on Test}) \quad (1.7$$

$$y = \log(\log(1/(1- \text{Median Rank}))) \quad (1.8)$$

The results of transformation are given in Table III.

Table III Plotting Positions for Weibull Graph

Hours on Test	log(Hours on Test)	Median Rank	log(log((1/(1 -M.R.)))
544.00	6.30	.07	-2.67
663.00	6.50	.16	-1.73
897.00	6.80	.29	-1.08
914.00	6.82	.41	-.64
1084.00	6.99	.56	-.18
1099.00	7.00	.72	.24

The data in Table III is then used to estimate the parameters of the Weibull Distribution. The graph of this data is shown in Figure 1.

```
     DOWN-L.Median Rank   ACROSS-L.Hours
              I                                          SYMBOLS :
          .24+                                     .      . = 1
              I                                    R$     : = 2
              I                                    .      * = 3
              I
              I
         -.62+                         .
              I
              I
              I                        .
        -1.30+
              I
              I
              I        .
        -1.98+
              I
              I
              I
       -2.67RL
             +R1------+------+------+-------++
              6.299     6.651          7.002
```

Slope = 3.72   Intercept = -26.06

beta = 3.72

$$\text{theta} = \exp(26.06)^{(1/3.72)} = 1102.544 \text{ Hours}$$

Figure 1. Scatter Plot of log of miles versus log of median plotting position with estimate of Weibull parameters.

Hazard Plotting

A second method of handling incomplete multi-censored data is called 'hazard plotting'. The name originates from the fact that the cumulative hazard function is used in the plot instead of the cumulative distribution function. The hazard function is also called the instantaneous failure rate, and is given by the expression

$$h(x) = (beta/theta)*(x/theta)^{(beta - 1)} \quad (1.9)$$

In a complete sample of n failure times there is a probability of 1/n associated with each failure time. Similarly, for an arbitrarily censored sample of failure times, there is a conditional probability of 1/K associated with each failure time which is the proportion of the K items that have experienced an observed age and then have failed at that time.

Data are prepared for hazard plotting in the following way

Step 1. Order the n values in the sample from smallest to largest without regard to whether they are observed or censored values. In the list of ordered values, the observed data are each marked to distinguish them from the censored values. If some observed and censored items have the same value, they should be listed in a random order.

Step 2. Number the order values in reverse order with n assigned to the smallest data value, n-1 to the second,etc. The values so obtained are called K values, or reverse order numbers.

Step 3. Obtain the corresponding hazard value for each observed value and record it. The hazard value for the observed value is 100 divided by its K value. Censored values do not have corresponding hazard values.

Step 4. For each observed failure value calculate the corresponding cumulative hazard value. This is the sum of the hazard value of that observed value and all preceding observed values.

Step 5. Perform a log transformation on both the observed failure value and its corresponding cumulative hazard value. The values of x and y for performing a linear regression are

$$\log(H) = \log(\text{cumulative hazard value}) \quad (1.10)$$

$$\log(y) = \log(\text{observed failure value}) \quad (1.11)$$

Perform a regression analysis on the values of log(y) and log(H). The expression for the resulting regression line is

$$\log(y) = (1/\text{beta})*\log(H) + \log(\text{theta}) \quad (1.12)$$

The Weibull parameter beta is the inverse of the slope of the line, the parameter theta can be found by setting the cumulative hazard function H to 100. As an example of this type of analysis consider the previous problem.

Table IV Data for Hazard Plotting

Hours on Test	Sequence	K	Hazard Function	Cumulative Hazard Function
544	F1	10	10.00	10.00
663	F2	9	11.11	21.11
802	S1	8		
827	S2	7		
897	F3	6	16.67	37.78
914	F4	5	20.00	57.78
939	S3	4		
1084	F5	3	33.33	91.11
1099	F6	2	50.00	141.11
1202	S4	1		

The data in Table IV is transformed using the linearizing transformations in equations 1.10 and 1.11. The results of this transformation are given in Table V.

Table V Plotting Positions for cumulative hazard distribution

Hours on Test	log(Hours on Test)	Cumulative Hazard Rate	log(C.H.R.)
544.00	6.30	10.00	2.30
663.00	6.50	21.11	3.05
897.00	6.80	37.78	3.63
914.00	6.82	57.78	4.06
1084.00	6.99	91.11	4.51
1099.00	7.00	141.11	4.95

The data in Table V is plotted in a scatter plot and regression analysis is performed to find the parameters of the regression line as shown in equation 1.12. The graph of this data is shown in Figure 2.

The results of the two methods of calculation are shown in Table VI. The difference between the two estimates is due largely to the different methods used in developing the average order of the data. With small samples such as that used in the example the error is larger than when applied to large samples which are typical of the SDC program.

```
DOWN-LOG.HOURS 'L'  ACROSS-LOG.CUM.HAZARD '1'
          I                             R$       SYMBOLS :
     7.002+                           .    .      . = 1
          I                                       : = 2
          I                                       * = 3
          I
          I                       .
     6.795+                  .
          I
          I
          I
     6.630+
          I
          I
          I      .
     6.464+
          I
          I
          I
     6.299R$
          ++-------+------+------+-------++
           2.30         3.63           4.95
```

Slope = .28 Intercept = 5.681

beta = 1/.28 = 3.57

theta = exp(.28 * log(100) + 5.68) =1065.64 hours

Figure 2. Scatter Plot of log of miles versus log of cumulative hazard function with estimate of Weibull parameters.

Table VI Comparison of Weibull Parameters Derived from the Cumulative Distribution Plot (C.D.P.) and the Cumulative Hazard Plot (C.H.P.)

Method	beta	theta (hours)	mean (hours)	standard deviation
C.D.P.	3.72	1102.54	995.29	298.14
C.H.P.	3.57	1065.64	959.82	298.37

Extreme Value Distribution

The usual life test consists of n components subjected to some specific operating environment until the units fail. If times to failure are recorded, an estimate of the parameters of the failure distribution can be made after all n components have failed. Testing time and cost can be reduced by terminating the test after a certain specific time or after a certain preassigned percent of the components have failed. If the test components are divided into N groups of n components each and the Nth group is removed from the test after the first failure of one component in that group the test data will consist of times to first failure. In the case of the SDC data each vehicle can be considered to be a group of n components and although during the SDC program more than one component has failed only the first failure time is chosen. Vehicles are frequently removed from the SDC program before experiencing a particular failure and, since the SDC is a continuing program, some units will still be under test without having had a failure. These vehicles will be treated as censored groups and analyzed using the methods for multi-censored data. These data will then form a distribution which will depend on the parent population from which the original group data is drawn. Extreme Value statistics will then be used to estimate the parameters of the parent distribution for the test component.

Consider a random sample of size n from a large population having as a parent distribution a cumulative distribution function F(x) where x is a continuous random variable. Let the sample be denoted as $x_1, x_2, \ldots, x_n$. Define the random variable

$$y_n = \min(x_1, x_2, \ldots, x_n) \qquad (1.13)$$

The random variable y_n is termed the smallest Extreme Value.

Since material or equipment failure is related to the weakest component, the Extreme Value distribution for the smallest value is the one usually encountered in reliability work, and is the one considered here. The cumulative distribution for y_n is given by

$$G_n(y) = 1 - [\ 1 - F(x)]^n \qquad (1.14)$$

Rearranging the terms of equation 1.14

$$F(x) = 1 - [1 - G_n(y)]^{1/n} \qquad (1.15)$$

In the case of the Weibull distribution

$$G_n(y) = 1 - \exp(-(x/\text{theta})^{\text{beta}}) \qquad (1.16)$$

Armored Vehicle Road Wheel Mortality Curves

Sample Data

The SDC program collects data from selected organizations that are performing their regularly assigned duties without any special test procedures or plans. This results in data that is difficult to analyze. Although the sample size tends to be constant vehicles leave and enter the sample for a variety of reasons. In some cases entire organizations are replaced. The result is that the sample consists of a constant number of vehicles with widely varying usage. The number of vehicles and their location is shown in Table VII.

Table VII SDC SAMPLE SIZE AND LOCATIONS

M1 TANKS

START DATE	STOP DATE	LOCATION MAJOR COMMAND	SITE CODE	SAMPLE SIZE
JAN 82	MAR 84	FT. HOOD, TX.	H	58
JAN 82	CONT.	SCHWEINFURG,FRG.	S	116
MAR 82	SEP 82	SCHWEINFURG,FRG.	R	58
APR 84	CONT.	FT. HOOD,TX.	C	58
OCT 84	CONT.	BAMBERG,FRG.	T	53

		TOTAL SAMPLE SIZE		343

M60A3 TANKS

START DATE	STOP DATE	LOCATION MAJOR COMMAND	SITE CODE	SAMPLE SIZE
OCT 79	JUN 82	FRIEDBERG,FRG.	F	110
NOV 79	DEC 80	WEISBADEN,FRG.	W	54
JAN 81	JUL 84	BAMBERG,FRG.	B	53
JUL 82	JUN 86	FT. STEWART,GA.	S	62
AUG 82	SEP 85	KIRCHGOENS,FRG	K	59

		TOTAL SAMPLE SIZE		338

M2/M3 BRADLEY

START DATE	STOP DATE	LOCATION MAJOR COMMAND	SITE CODE	SAMPLE SIZE
FEB 84	OCT 85	FT. HOOD,TX.	A	60
NOV 83	CONT.	FT. HOOD,TX.	B	60
OCT 83	CONT.	KITZINGEN,FRG.	C	60
JAN 84	CONT.	KITZINGEN,FRG.	D	6
JAN 84	CONT.	KITZINGEN,FRG.	E	6
MAY 84	CONT.	ASCHAFFENBURG,FRG.	F	60
NOV 85	CONT.	FT. HOOD, TX.	G	60

		TOTAL SAMPLE SIZE		312

Note: Data used in this report is as of 5/1/86.

All sampling inquiries are aimed at learning something about a particular parent population. In order to properly analyze the data there must be some assurance that all the data is from the same population. In the case of the M1 and the M2/M3 the samples are drawn from new vehicles and we can be reasonable sure the that the only biasing factor is the various base locations. In the case of the M60A3 there are several other factors that could bias the data. Some of the M60A3 tanks are new, some have been converted at depots, some at Mainz and some at Anniston. The road wheels on the converted tanks may not have been replaced at the depot. There are also three type of road wheels one of steel, and two of aluminum. The effects of these factors on road wheel failure times must be determined and removed before the mortality curves can be developed.

The demographics of the vehicles in SDC may also bias the data, in Figure 3 the distribution of miles per vehicle are shown, and it is easily seen that the miles driven in SDC vary widely. Another factor biasing the data is due to the variations in the time the vehicles were in the sample. The distributions of the vehicles by the time of arrival and departure are shown in Figures 4,5 and 6.

M60A3

The M60A3 program was initiated in September 1979. The program proceeded unsteadily until December 1982 when new forms were developed and the program assumed a degree of stability. The data collected prior to Dec. 82 at the Weisbaden and Friedberg sites has generally been considered unreliable. For this reason the data at these sites was not considered in the current analysis. The distribution of new and converted tanks between the remaining bases was not uniform. The tanks at Bamberg were all new. The tanks at Ft. Stewart were all converted at Anniston. The tanks at Kirchgoens included 10 new tanks and the remainder were converted at Mainz. Because of this distribution of tanks the Base and the New or Converted effects are not independent and cannot be separately removed from the data to allow other less significant effects to be studied. To confirm that the effects are not independent the results of a Contingency Test for Independence are shown in Figure 7.

The history of the road wheels on the converted M60A3's isn't known. Some road wheels may be new, but most of them are probably the same wheels the tanks had prior to conversion. These significant effects cannot be removed because of their interdependence. Consequently only the SDC data on the new M60A3 tanks that have only steel road wheels was considered in this analysis.

	NEW	CONV.		TOTAL		
BAMBERG	50.0	0.0	:	50	-	ACTUAL
	18.6	31.4	:		-	EXPECTED
FT. STEWART	0.0	58.0	:	58		
	21.6	36.4	:			
KIRCHGOENS	10.0	43.0	:	53		
	19.8	33.2	:			
TOTAL	60.0	101.0	:	161		

Figure 7. Contingency test for independence of Base and New Effects. If effects were independent actual values would more closely equal expected values.

Analysis of the significance of the Base Effect on the replacement times of road wheels is shown in Figure 8. A useful index for quantifying the amount of total variability that can be attributed to differences between groups is the Eta statistic:

$$\text{Eta}^2 = \frac{\text{Between Groups Sum of Squares}}{\text{Total Sum of Squares}}$$

The maximum value of Eta-squared is 1, while the minimum is 0. An Eta-squared of close to 1 indicates that most of the observed variability is due to differences between groups, not within the groups. An Eta-squared value of .04, shown in Fig. 8, indicates that the variation in replacement time is not significantly affected by the vehicle location, and the data from the two bases can be pooled to develop the road wheel- mortality curve. This conclusion is supported by the analysis of variance (ANOVA) also shown in Figure 8.

```
PLOT OF MILES BY BASE   * = MEAN   U/L = MEAN +/- 1 STD DEV
            3200 -                              .
                 :      U                       .
                 :                              .     U
    M       2700 -                              .
    I            :                              .
    L            :                     U        .
    E       2200 -       *                      .      *
    S            :                              .
                 :                     *        .
            1700 -                              .
                 :      L                       .     L
                 :                     L        .
            1200 -------:-----------:----.----:
    BASE->          BAMBERG     KIRCHGOENS    TOTAL
```

Figure 8. Analysis of Base Effects on Replacement times of road wheels of new M60A3 tanks. Eta SQRD = .044

The Eta Squared Statistic shows that only 4 percent of the variation can be attributed to the base effect and therefore it can be concluded that the Base Effect is not significant.

M1 Data

The M1 SDS began in January 1980 and is still continuing. Some of the factors that confound the M60A3 data are also present in the M1 data, however analysis of the M1 data produces an Eta-squared value of .09. This would indicate that the Base Effect contributes more variation than in the M60A3 case, however since there are more bases from which the data is collected, this increase in Eta could be expected so that the data from these bases can also be pooled to develop road wheel mortality curves.

M2/M3 Data

The M2/M3 SDS began in October 1983 and as a result benefited from the experience of the M60A3 and the M1. This enabled the SDC teams to achieve a higher degree of reliability than had been evident in the previous data collecting efforts.

Samples used in Road Wheel Mortality Analysis

The sample data used in the road wheel analysis is summarized in Tables VIII,IX, and X. The number of vehicles leaving the SDC sample during a 250 mile interval and the number of first replacements occurring in the interval for each of the three vehicles are listed. The vehicles leaving the sample with out exhibiting a road wheel failure are listed as censored data. In the case of the M1 and M2/M3 all the available data was used. In the case of the M60A3 only the data from newly manufactured tanks was used.

Table VIII Distribution of M60A3 Tank Data Used in Road wheel Analysis

Miles In SDC	Censored Vehicles	1st Road Wheel Failure
250	0	0
500	1	0
750	2	1
1000	1	0
1250	2	1
1500	4	2
1750	4	2
2000	2	0
2250	2	3
2500	0	2
2750	2	3
3000	0	9
3250	1	10
3500	1	10
3750	1	7
4000	0	3
TOTAL	23	57

Table IX Distribution of M1 Tank Data
Used in Road wheel Analysis

Miles In SDC	Censored Vehicles	1st Road Wheel Failure
250	4	0
500	2	1
750	10	2
1000	9	0
1250	26	16
1500	20	20
1750	5	25
2000	12	20
2250	15	33
2500	8	35
2750	4	17
3000	0	16
3250	0	12
3500	0	6
TOTAL	115	203

Table X Distribution of M2/M3 Bradley Data
Used in Road wheel Analysis

Miles In SDC	Censored Vehicles	1st Road Wheel Failure
250	3	0
500	3	0
750	4	0
1000	5	1
1250	6	7
1500	27	7
1750	14	7
2000	15	4
2250	15	10
2500	11	7
2750	12	10
3000	12	20
3250	16	25
3500	7	18
3750	8	12
4000	9	11
4250	3	10
4500	0	1
4750	0	2
5000	0	0
TOTAL	170	152

There are two factors that require investigation before developing the mortality curves. These are the Base Effect and the M2/M3 Effect. The Eta-squared analysis was performed on the M2/M3 data. The results of this analysis produced an Eta-squared value for the variation due to the difference between the M2 and the M3 of .0001, a value which is clearly not significant. The Base Effect produced an Eta-squared value of .095, some what higher than the M1, but again with the increased number of bases and the resulting decrease in sample size such a value can be expected without being significant.

Hazard Analysis of Tracked Vehicle Road Wheel Replacements

The method of analysis used to estimate the parameters of the road wheel mortality curves is called 'hazard analysis' The term 'hazard analysis' originates in the analysis of the instantaneous failure or replacement rate. This is the failure or mortality rate in a population at a specified level of stress or at a specified time. The hazard function is an algebraic relationship of two probability functions: the density function and the survival function. The hazard function is defined as:

$$h(x) = \frac{f(x)}{1 - F(x)}$$

Where $h(x)$ = the hazard function

$f(x)$ = the probability density function

$F(x)$ = the cumulative distribution function

$1 - F(x)$ = the survival function

A separate road wheel data base was generated from the SDC data. From this data base two files were created for each vehicle. One file is a historical file containing the date that the vehicle entered SDC and the latest data that it appeared in the quarterly or monthly report. The second file is a list of all the replacement reports for the vehicle road wheels. To simplify the analysis several utility programs were written to prepare the data for regression analysis. The regression analysis was then performed using an interactive statistical software package. The curves in Figures 9 through 11 show the results of the calculations for the M60A3,the M1, and the M2/M3, which were developed using this program. From the slope and intercept of the curves estimates of the shape and scale parameters of the associated Weibull distributions shown in Table XI were developed.

Table XI
Parameters of the Smallest Extreme Value
Weibull Distributions of Tracked Vehicle Road Wheels

Vehicle	NSN	Army Ordnance Number	Mean (Miles)	Standard Deviation	Beta	Theta
M1	2530-01-063-5824	12274492	2158.04	777.368	3.03	2158.0
M60	2530-00-701-3976	7013976	3107.98	871.92	4.00	3428.9
M2/M3	2530-01-801-6702	10919004	3207.89	1060.30	3.33	3574.4

```
DOWN-LOG OF MILES   ACROSS-LOG OF CUMULATIVE HAZARD FUNCTION
          I                                 RP    SYMBOLS :
      8.53+                                 RM     . = 1 - 2
          I                                .      : = 3
          I                             ...      * = 4
          I                          .*::.
          I                       ***:
      7.96+                   ..::
          I                 ..
          I               ..
          I               .
      7.51+
          I             ..
          I          ..
          I
      7.06RM   .
          RP
          ++--------+------+------+-------++
           .25       3.18        6.12
               SLOPE = .25 INTERCEPT = 6.99
                    beta = 1/.25 = 4.00
        theta = exp(.25 * log(100) + 6.99) = 3428.92 miles
```

Figure 9. Scatter Plot of log of miles versus log of cumulative hazard function with estimate of Weibull parameters for road wheels of M60A3 tank.

```
DOWN-LOG OF MILES ACROSS-LOG CUMULATIVE HAZARD FUNCTION
    I                                 R$      SYMBOLS :
8.21+                                 ...     . = 1 - 6
    I                              .::.       : = 7 - 11
    I                            .*:           * = 12 - 17
    I                          :**
    I                        :*.
7.43+                      .*.
    I                     .:
    I                   .:.
    I                 ...
6.80+                 .
    I             ....
    I          ...
    I       ..
6.18+
    I
    R$      .
    ++--------+------+-------+--------++
     -1.17        2.58          6.32
          SLOPE = .33 INTERCEPT = 6.27
               beta = 1/.33 = 3.03
  theta = exp(.33 * log(100) + 6.27) = 2415.61 miles
```

Figure 10. Scatter Plot of log of miles versus log of cumulative hazard function with estimate of Weibull parameters for road wheels of M1 Tank.

```
DOWN-LOG OF MILES ACROSS LOG OF CUMULATIVE HAZARD FUNCTION
                                                R$    SYMBOLS :
8.33+                                          .      . = 1 - 4
    I                                        **:.     : = 5 - 8
    I                                     :**.        * = 9 - 12
    I                                   .*:
    I                                 .**
7.71+                               :::
    I                             ::
    I                           ..
    I                          .
7.22+                        ..
    I                       ..
    I                     ..
    I
6.72+
    I                   ..
    RM          . .
    RP
    ++--------+-------+-------+--------++
     -1.16        2.08          5.32
          SLOPE = .30 INTERCEPT = 6.80
               beta = 1/.30 = 3.33
  theta = exp(.30 * log(100) + 6.80) = 3574.39 miles
```

Figure 11. Scatter Plot of log of miles versus log of cumulative hazard function with estimate of Weibull parameters for road wheels of M2/M3 Bradley.

Estimation of the Parameters of the Population Weibull Cumulative Distribution

In Table XI the parameters of the smallest Extreme Value distribution of the vehicle road wheels are listed. When these values are known the parameters of the population distribution can be estimated using the following expressions. The cumulative distribution of y_n where y_n is the smallest Extreme Value is:

$$G_n = 1 - [1 - F(y)]^n$$

where F(y) is the population cumulative distribution. Rearranging and substituting

$$1 - \exp^{-(y/\text{theta})^{\text{beta}}}$$

for $G_n(y)$ the population distribution becomes:

$$F(y) = 1 - \exp^{-(y/\text{theta}*n^{1/\text{beta}})^{\text{beta}}}$$

The parameters for the distribution F(y) are:

slope parameter = beta

shape parameter = theta * $n^{1/\text{beta}}$

Using the values of the smallest Extreme Value parameters in Table XI the parameters of the population distribution functions can be developed. The values of the population parameters are given in Table XII. Substituting these parameters in the equation for the Weibull probability density function, shown in equation 1.1a, the density functions for the road wheel distributions as shown in Figure 12. can be developed.

Table XII
Parameters of the Population Weibull Distributions of Tracked Vehicle Road Wheels

Vehicle	NSN	Mean (Miles)	Standard Deviation	Beta	Theta
M1	2530-01-063-5824	6051.09	2179.72	3.03	6773.3
M60	2530-00-701-3976	6480.25	1818.00	4.00	7149.4
M2/M3	2530-01-801-6702	7830.95	2591.17	3.33	8726.0

The probability density functions shown in Figure 12 have been normalized for easy comparison. From these curves it can be seen that there is little difference between the M60A3 and the M1 road wheel mortality curves, while the M2/M3 road wheels show a some what higher expected life.

Cost and Effectiveness of Block Changes of Tracked Vehicle Road Wheels

Road wheel mortality curves developed from SDC program data have been used as input to a life cycle cost simulation model developed by the Systems and Cost Analysis Directorate of the U.S. Army TACOM. The life cycle costs of road wheel changes have been developed for a variety of block change cycles and useful life policies. The effect of these policies on the mean-miles-between unscheduled replacements and road wheel availability have been calculated.

Analysis

The Life Cycle Costs (LCC) of various Block Change policies were developed using the mortality data developed in this report and the values of the cost and maintenance parameters in Table XIII. This data was used in a LCC simulation model developed for the TACOM Systems and Cost Analysis Directorate. The LCC costs were developed for different combinations of miles between block changes and tank operation miles. The LCC results are presented in Figure 13, which shows that block change policies do not provide any cost benefit over unscheduled replacement. Even though there is no direct cost advantage in block replacement, there might be some increase in systems effectiveness. The elements of system effectiveness which will effect readiness are the times between maintenance actions such as wheel replacement and the elements of availability contributed by the road wheels.

Systems availability may be computed using the following expression:

$$As = \frac{(\text{total operating time})}{(\text{total operating time}) + k^*(\text{total down time})}$$

where

As = Systems availability.

if $0 < k < 1$, free time exists

if $k = 1$, no free time exists

The case where no free time exists represents a situation where there is no possibility of performing maintenance during time when operation of the system is not required. The factor k would only equal 1 when the system would be operating continuously(ie. 24 hours per day). Since this would generally not be the case for wheeled vehicles the value of k would be much less than 1 and the reduction of down time would not have a large impact on the availability of the vehicle.

TABLE 1.
EXAMPLE OF VALUES OF PARAMETERS USED IN M1 SIMULATION

COST PER MAN HOUR	$9.92
BLOCK CHANGE RECOVERY RATE	1.00
COST OF REBUILT WHEEL	$153.00
FAILURE RECOVERY RATE	0.64
COST PER ROADWHEEL	$252.72
MAN HOURS PER BLOCK CHANGE	24.00
MAN HOURS PER FAILURE	1.00
NUMBER OF ROAD WHEEL POSITIONS	8
CONFIDENCE LEVEL 0.00 AND INDEX	3
MILES BETWEEN BLOCK CHANGES	1000
MAXIMUM COST CONFIDENCE INTERVAL	$500.00
TANK OPERATION MILES	15000
RANDOM NUMBER SEED	59873
MAXIMUM ITERATIONS	120

Another measure of effectiveness is called the intrinsic availability. The formula for calculation the intrinsic availability is given by the ratio:

$$Ai = \frac{(\text{total operating time})}{(\text{total operating time}) + (\text{total down time})}$$

This expression is similar to the expression for systems availability with the omission of the k factor.The effect of of reduced downtime due to block changes increases intrinsic availability and it can be seen that the intrinsic availability peaks between 3000 and 4000 mile block change interval. The increase in Ai ,however, is very small and its impact on tank availability would probably not warrant the increased costs.

The effect of road wheel replacement policies on mean miles between unscheduled replacement (MMBUR) is much more dramatic as shown in Figure 15. This shows that the MMBUR with 1000 mile block change policy is over 3000 miles but in this 3000 mile period there would be 3 block changes resulting in a MMBR as shown in Figure 16. There is still a substantial increase in MMBR but not nearly as dramatic as that increase in Figure 15.

The increase in intrinsic availability shown in Figure 14. results from a decrease in total downtime. The relationship of downtime to the block change interval is shown in Figure 17. With a block change policy between 1750 and 2000 miles the downtime is higher than that of random replacements, above 2000 miles the downtime with block changes is less than that with random changes, with a minimum at 4000 miles.

There are many factors to consider in deciding which policy is the best, block change or unscheduled random replacement. In every case the block change policy cost is

greater than the unscheduled replacement, however the block change policies can result in a longer time between replacement and a lower downtime. These factors can not be evaluated without consideration of their effect on system performance. If the downtime resulting from failure of other tank systems is large and the mean time between failure is substantially less, then the advantages of block change will be lost in the noise. The increase in cost however can not be ignored. Within the limits of this study we can not conclude that block change policies provide any advantage over an unscheduled replacement policy. Therefore we can not recommend the block change policy.

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FIGURE 3. NUMBER OF OF VEHICLES IN SDC PROGRAM 5/1/86

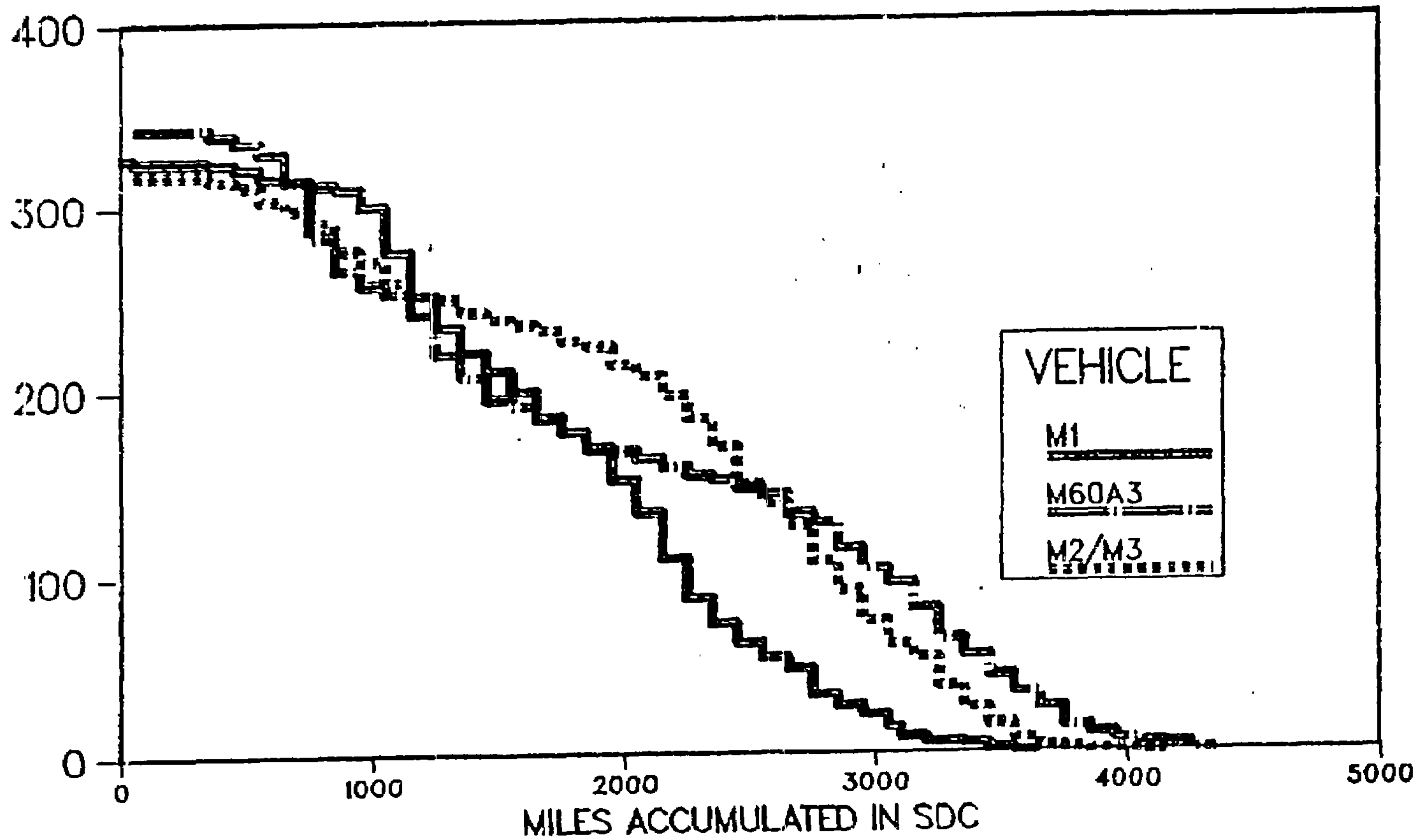


FIGURE 4. DISTRIBUTION OF M1 TANKS IN SDC
NOTE: HEIGTH OF BAR PROPORTIOAL TO NUMBER
OF VEHICLES IN BLOCK

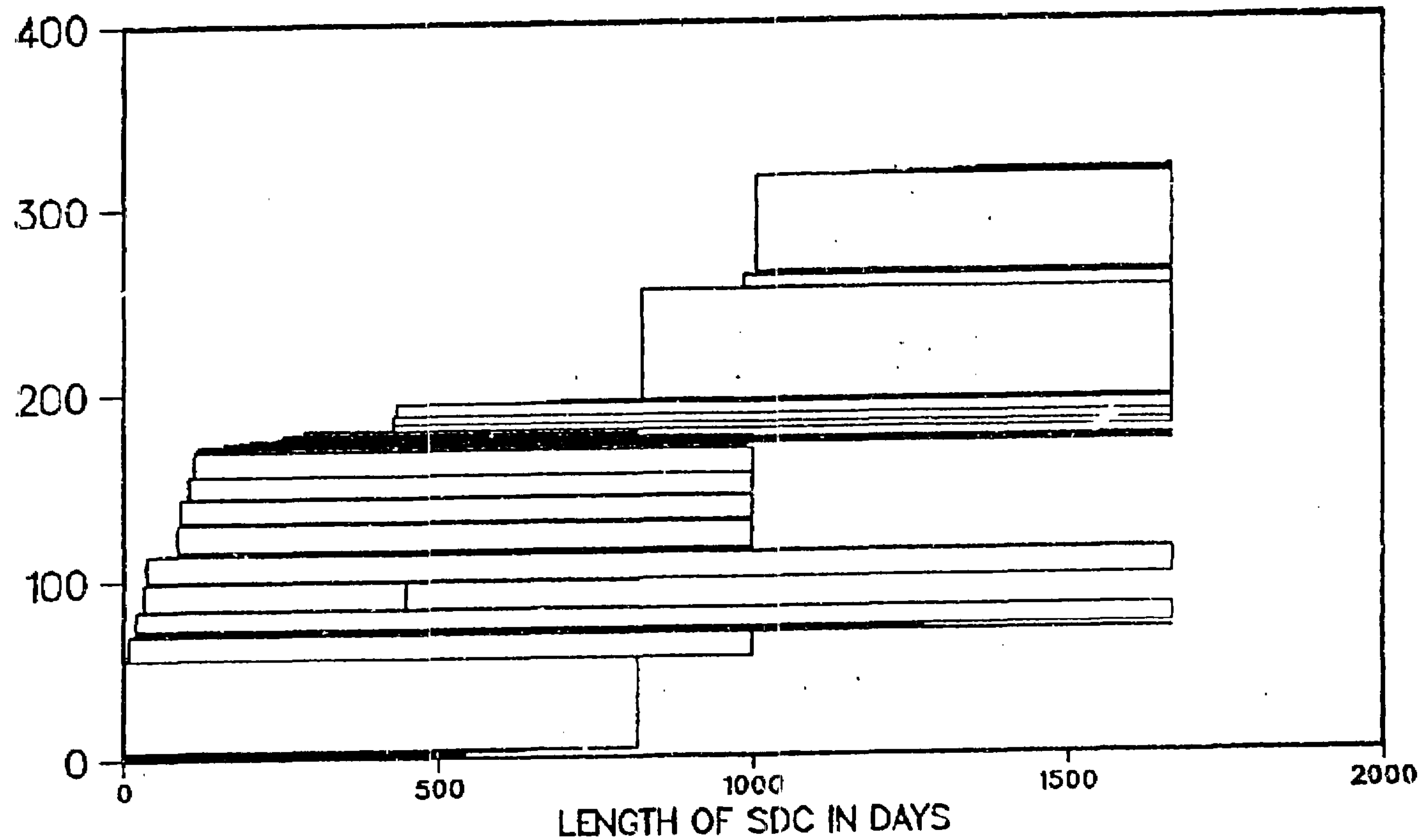


FIGURE 5. DISTRIBUTION OF M60 VEHICLES IN SDC
NOTE: HEIGTH OF BAR PROPORTIOAL TO NUMBER
OF VEHICLES IN BLOCK

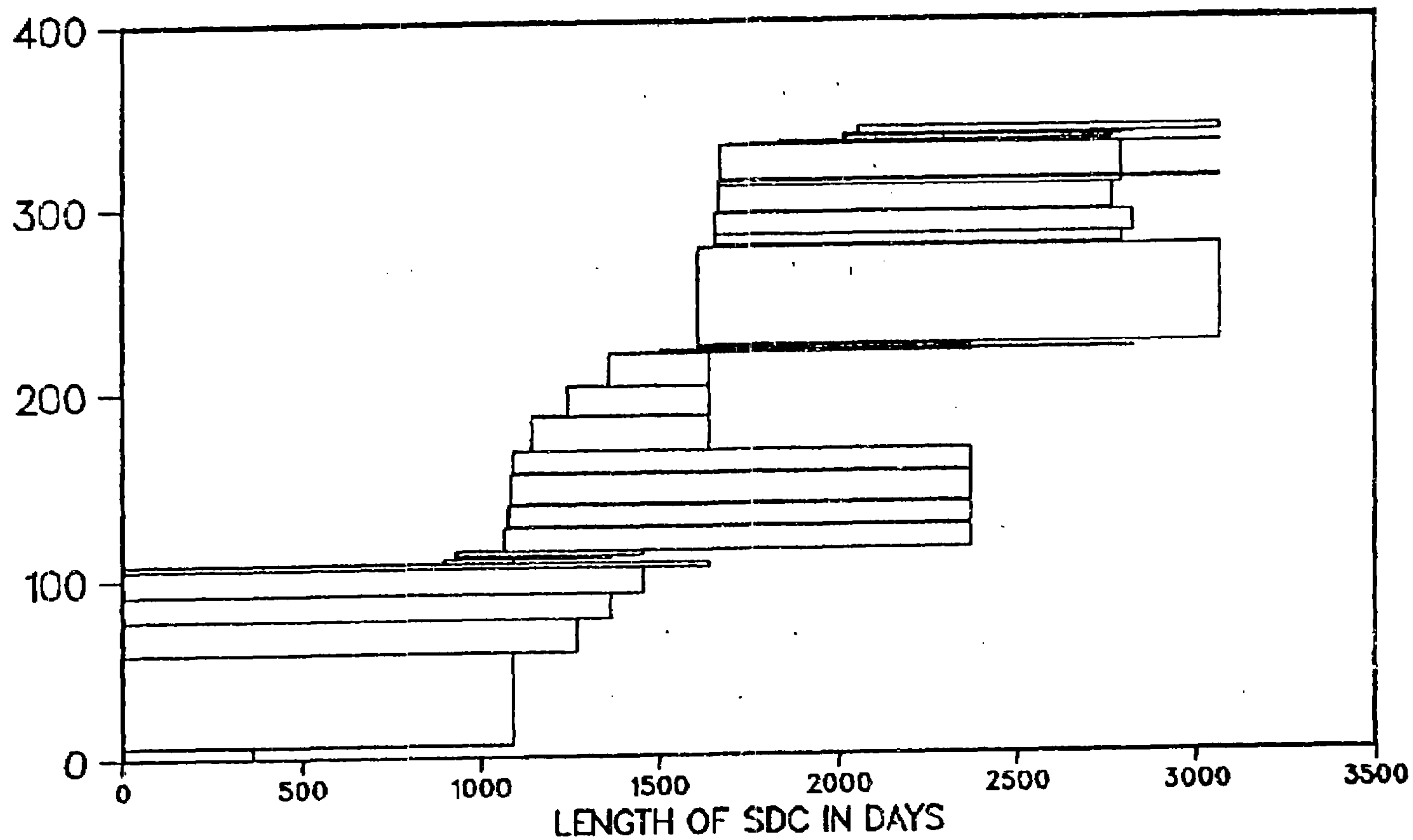


FIGURE 6. DISTRIBUTION OF M2/M3 VEHICLES IN SDC
NOTE: HEIGTH OF BAR PROPORTIOAL TO NUMBER
OF VEHICLES IN BLOCK

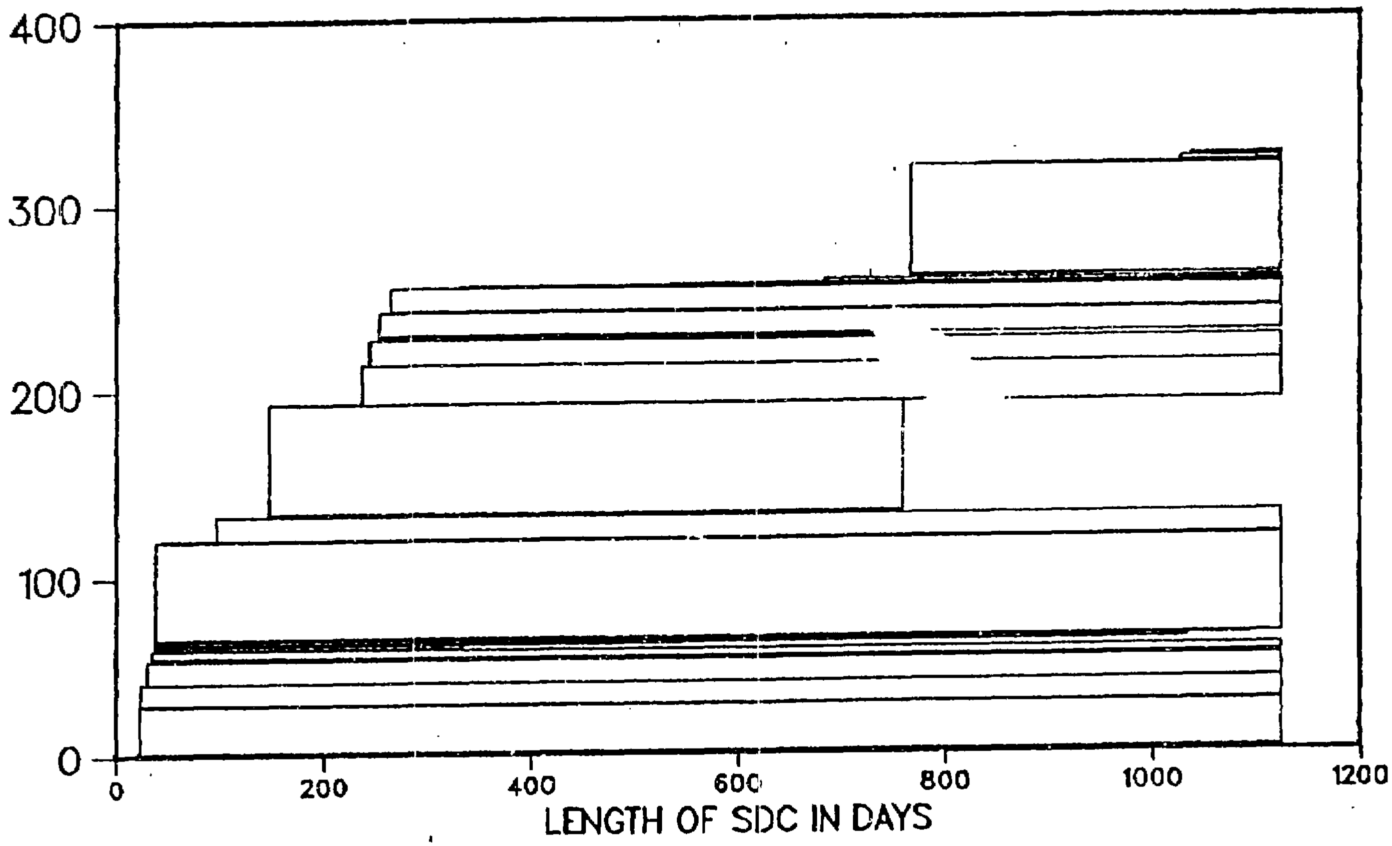


FIGURE 12. WIEBULL PROBABILITY DENSITY FUNCTIONS
FOR TRACKED VEHICLE ROAD WHEELS

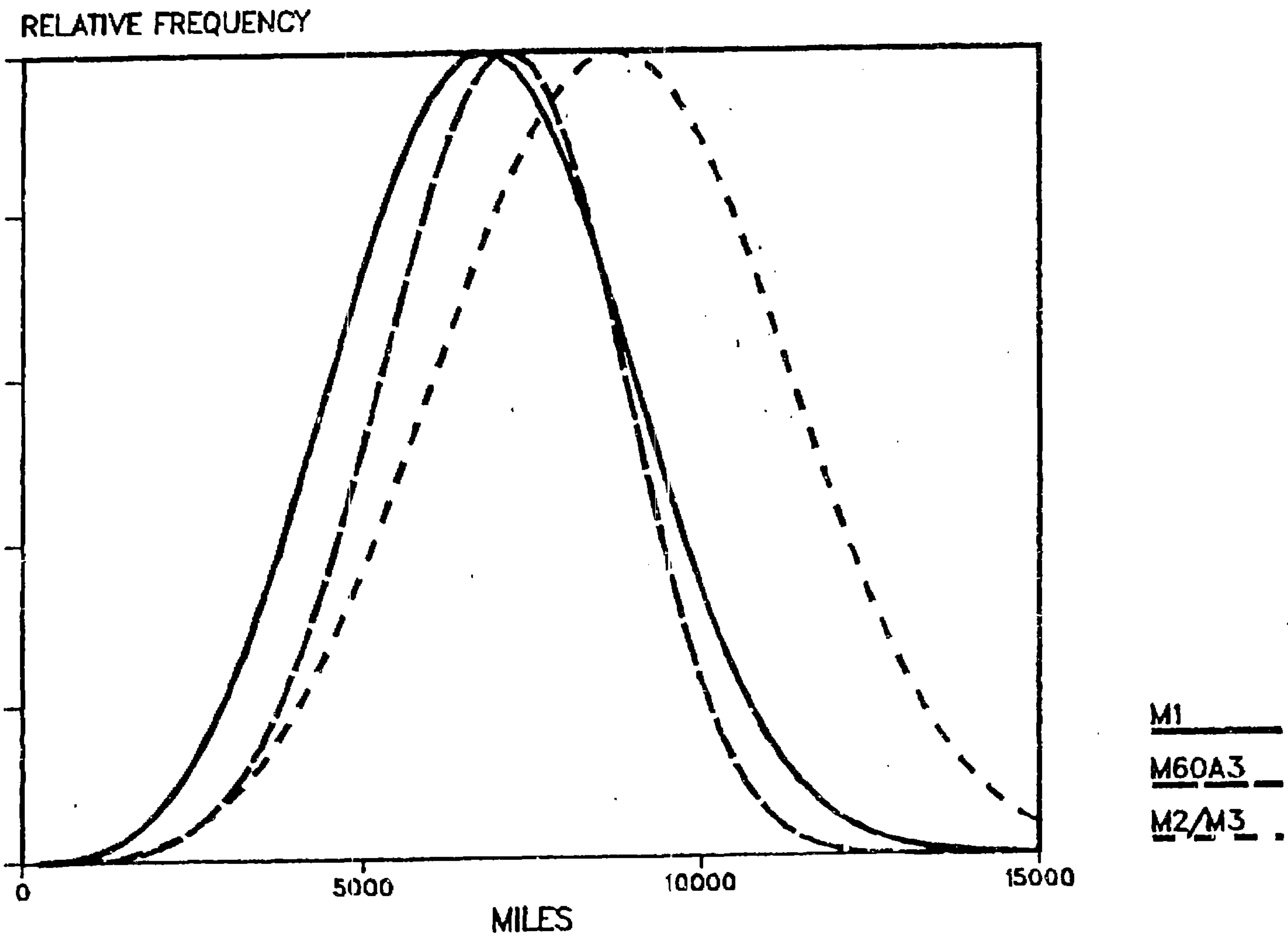


FIGURE 13. COST OF ROAD WHEEL BLOCK CHANGES
IN M1A1 TANK
NSN = 2530-01-063-5824

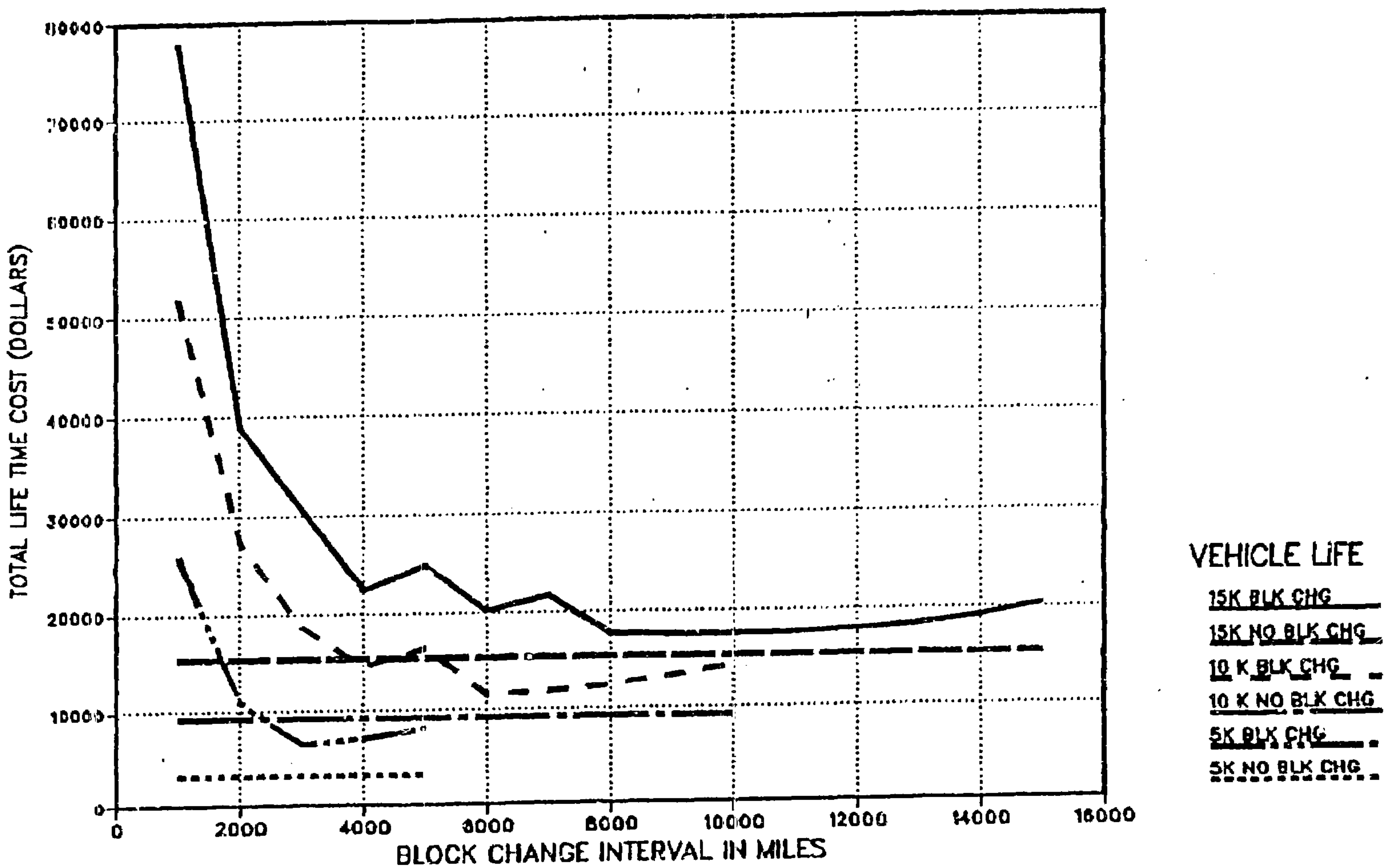


FIGURE 14. INTRINSIC AVAILABILITY OF M1A1 ROAD WHEEL SYSTEM AS A FUNCTION OF ROAD WHEEL BLOCK CHANGES NSN = 2530–01–063–5824

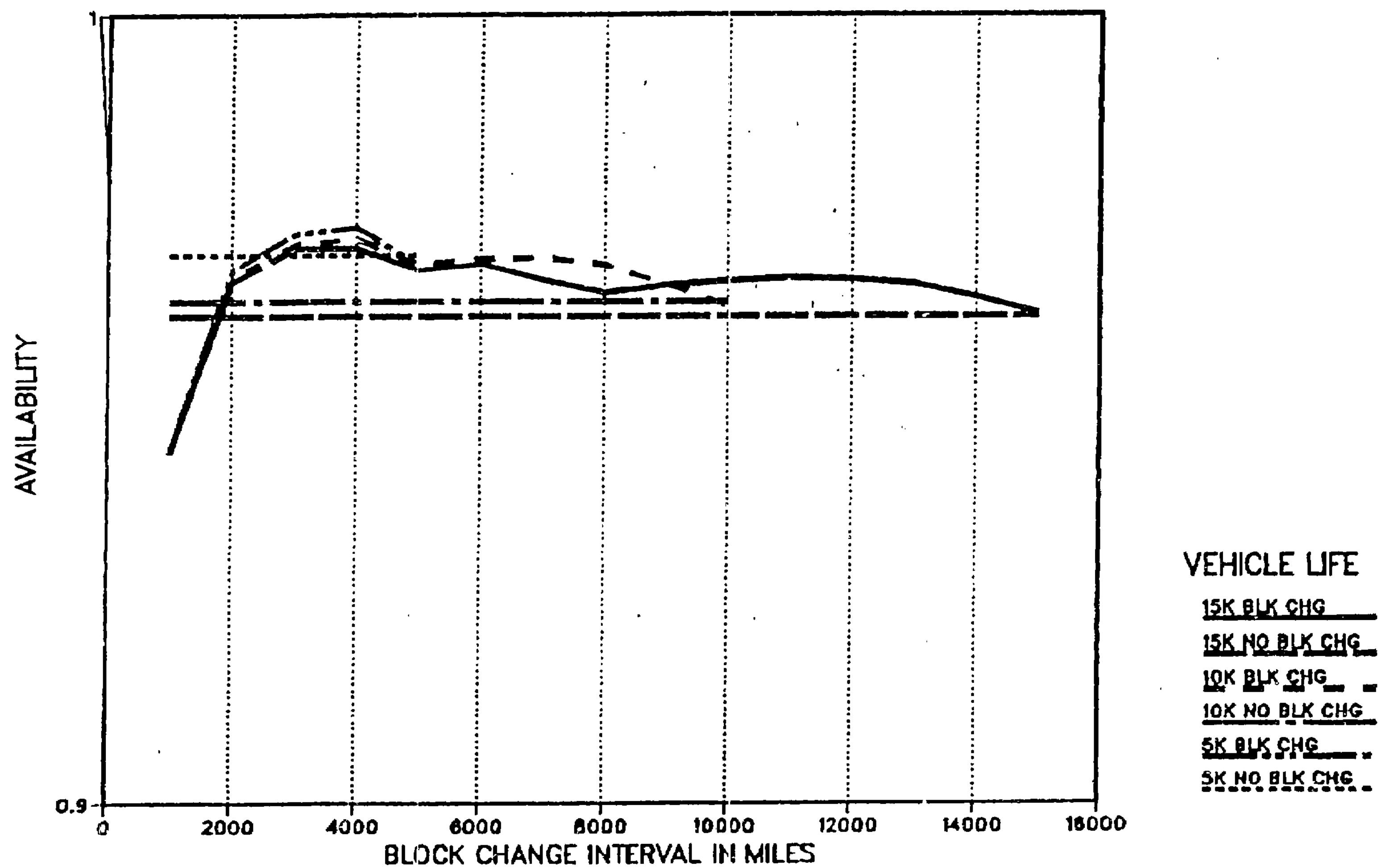


FIGURE 15. MEAN MILES BETWEEN UNSCHEDULED REPLACEMENT AS A FUNCTION OF ROAD WHEEL BLOCK CHANGES M1A1
NSN = 2530–01–063–5824

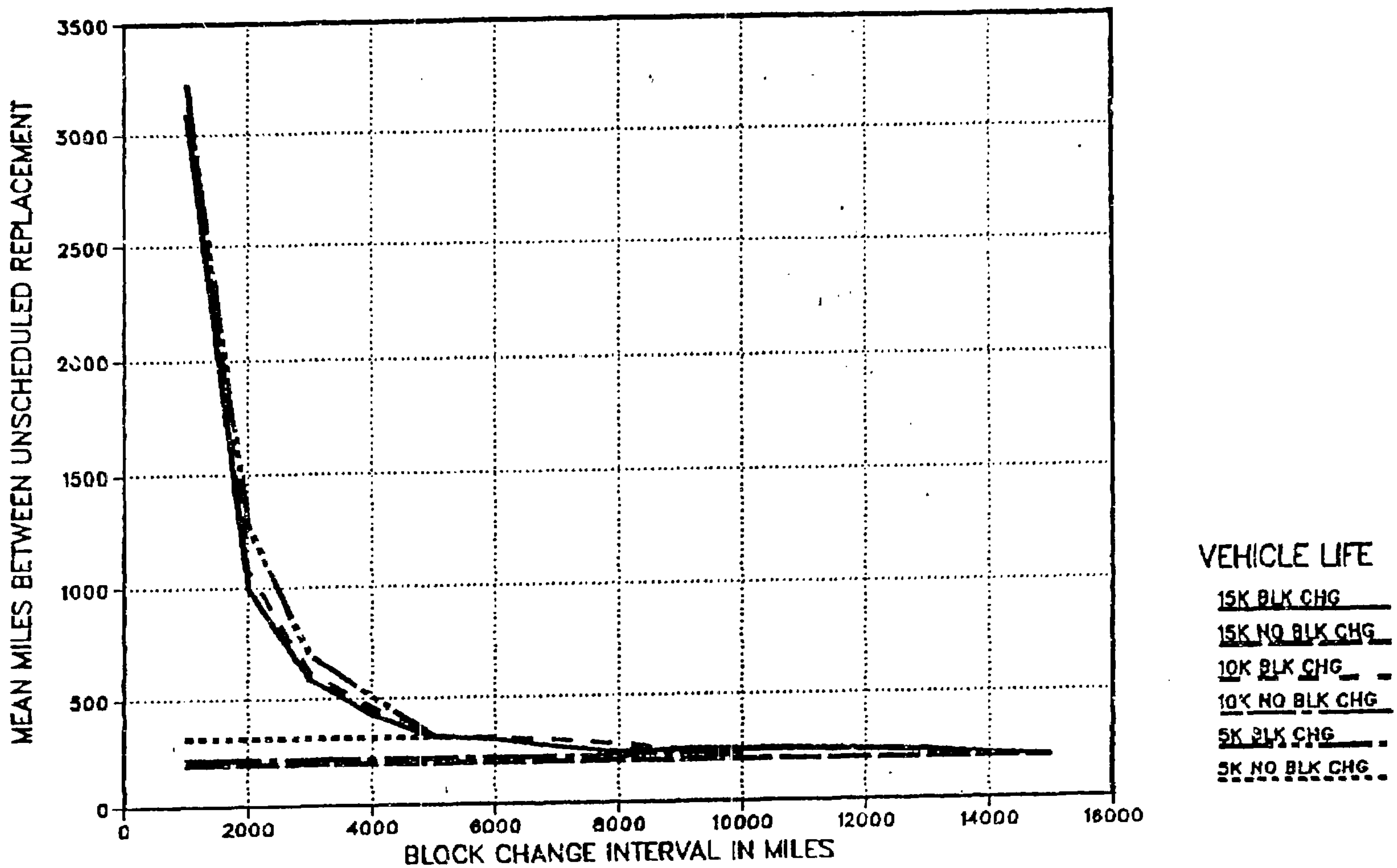


FIGURE 16. MEAN MILES BETWEEN REPLACEMENT
AS A FUNCTION OF ROAD WHEEL BLOCK CHANGES M1A1
NSN = 2530-01-063-5824

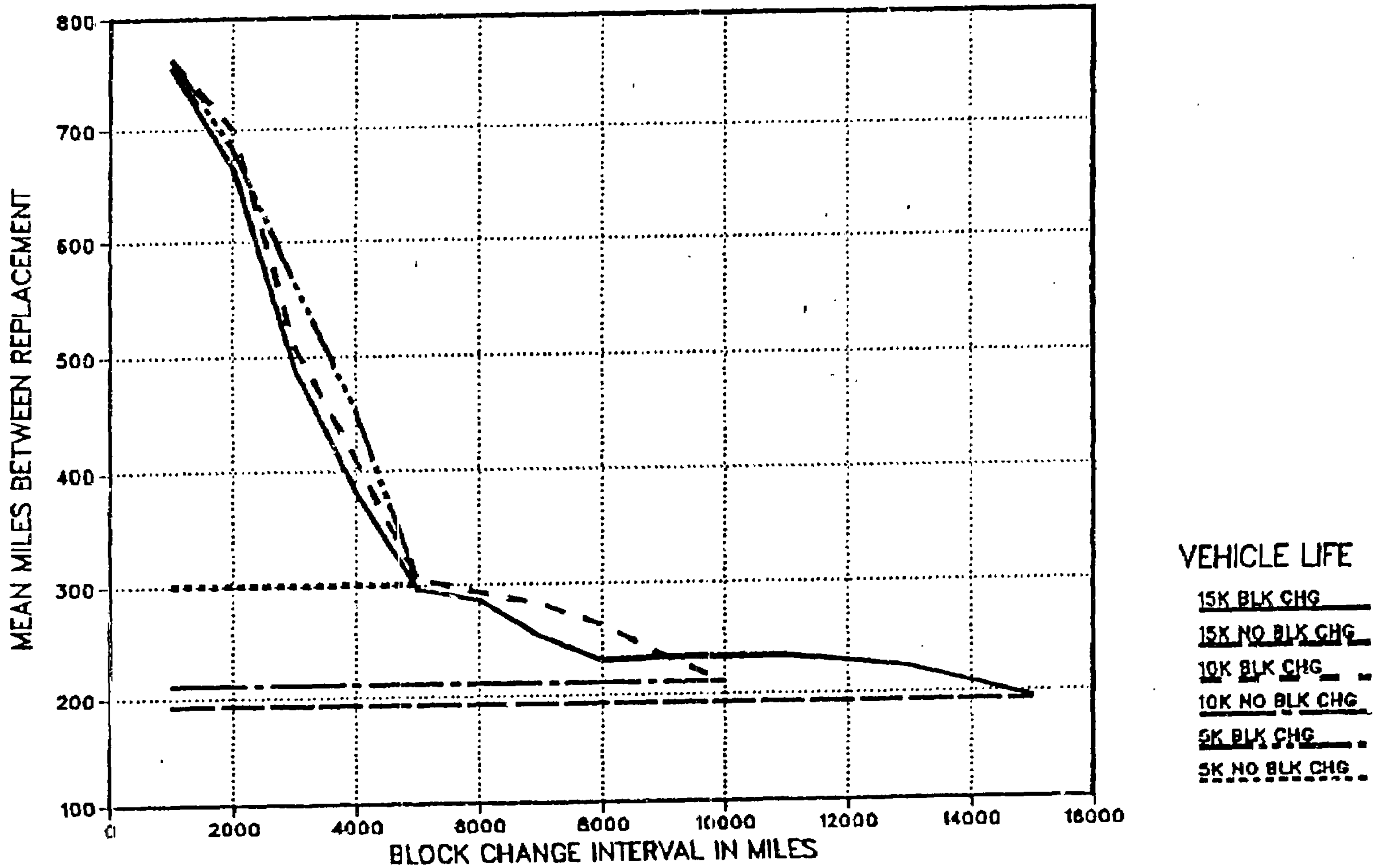
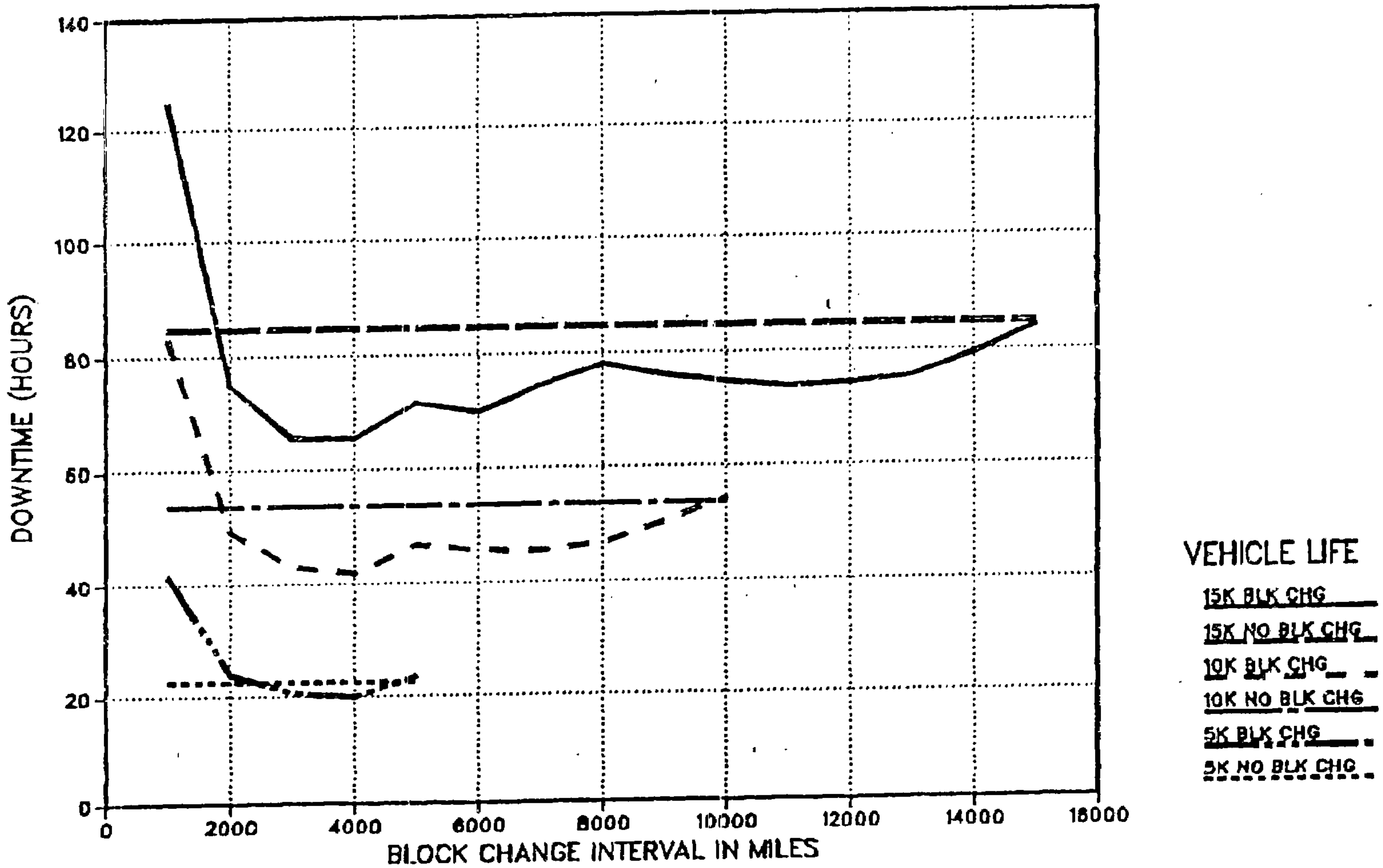


FIGURE 17. TOTAL ROAD WHEEL MAINTENANCE DOWNTIME (HOURS) AS A FUNCTION OF ROAD WHEEL BLOCK CHANGES M1A1
NSN = 2530–01–063–5824



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